

# **RESUME SCORING USING NLP**

## **PROJECT REPORT**



**VIT<sup>®</sup>**  
**Vellore Institute of Technology**  
(Deemed to be University under section 3 of UGC Act, 1956)

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## **ABSTRACT**

The objective of the project is to create a Resume Scoring algorithm using Natural Language Processing. The algorithm will parse resumes one by one and will create a Candidate Profile based on the skills mentioned in the resume.

A corpus is created using Sketch Engine, Wikipedia pages for various required skills (example : Machine Learning, Data Science, Software developer, Programming) are given as input,

Sketch Engine creates a corpus from the useful data available on the given links.

Word Embeddings are created from the corpus and these are used to match the skills in the candidate resume with the required skills.

Finally, the candidate profile is built and plotted as a bar graph for better visualization.

## Workflow

1. Creating corpus using Sketch Engine
2. Preprocessing
3. Removing common words that are not required
4. Creating phrases of words that frequently occur together (bigrams)
5. Creating word embedding using Genism , Word2Vec
6. Testing the model
7. Extracting resumes (using PyPDF) and converting to string
8. Building candidate profile using `model.most_similar(skills)`, where `skills` is an array of required skills and Creating a matcher using `Spacy` to match the words in resume to `most_similar(skills)`
9. Counting words under each category to build a candidate profile.
10. Printing and visualizing the candidate profile

### 1. Creating corpus using Sketch Engine

Sketch Engine is an online tool to analyse how language works. Its algorithms can analyse authentic texts of billion words to identify what is typical in a language, or rare or usual or emerging. It is used to create the corpus for our application since the available corpus did not contain the required words. Wikipedia pages are given as input and a text corpus is created from the useful information available on the given pages.

SINGLE-WORDS

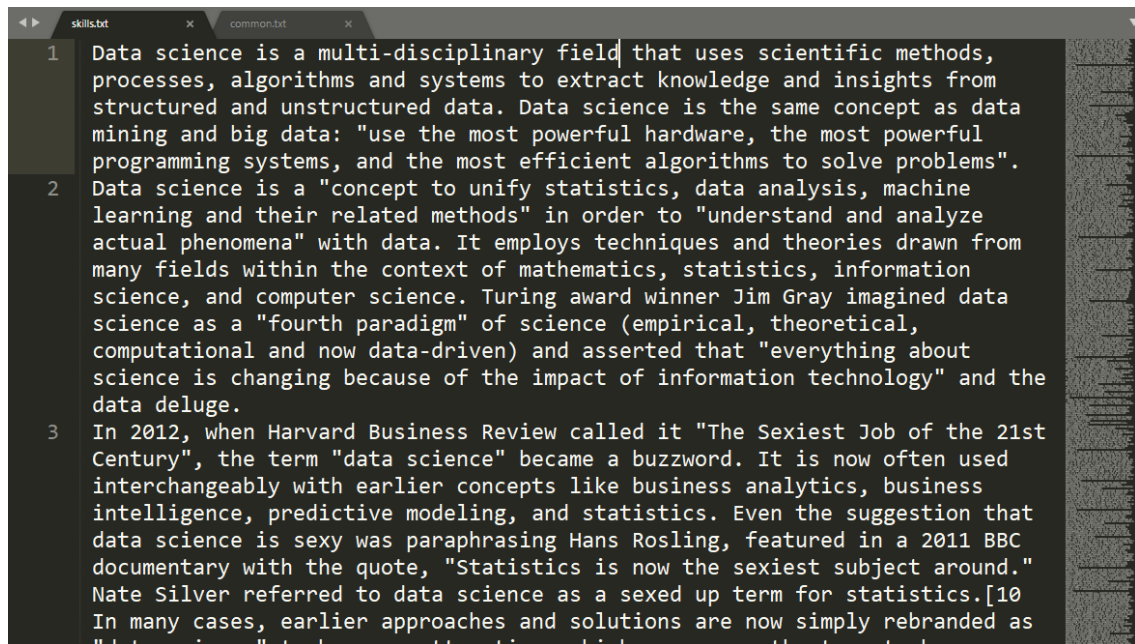
Word	Focus corpus	Reference corpus
1 doi	37	5,020 ...
2 Neural	19	4,975 ...
3 DNN	16	3,376 ...
4 neural	62	82,246 ...
5 LSTM	13	113 ...
6 arXiv	13	2,130 ...
7 PMID	11	4,425 ...

MULTI-WORDS

Word	Focus corpus	Reference corpus
1 deep learning	49	34 ...
2 data science	25	25 ...
3 neural network	18	74 ...
4 speech recognition	15	152 ...
5 programming language	16	474 ...
6 deep neural network	5	0 ...
7 software development	24	1,150 ...

Back to the original interface

Corpus :



## 2. Preprocessing

Skills.txt is preprocessed before creating word embeddings, it involves removal of white space, stop words, digits etc and <p> tags.

### Preprocessing

```
1 x=[]
2 for line in content:
3     tokens=word_tokenize(line)
4     tok=[w.lower() for w in tokens]
5     table=str.maketrans('','',string.punctuation)
6     strpp=[w.translate(table) for w in tok]
7     words=[word for word in strpp if word.isalpha()]
8     stop_words=set(stopwords.words('english'))
9     words=[w for w in words if not w in stop_words]
10    x.append(words)
```

## 3. Removing common words that are not required

A text file is created named common.txt which contains all the words that occur frequently and are not useful for technical skill matching (source : Wikipedia)

#### Removing commonly occurring words that are not useful

```
1 with open('common.txt') as f:
2     content2 = f.read()
3     ntexts=[]
4     l=len(texts)
5     for j in range(l):
6         s=texts[j]
7         res = [i for i in s if i not in content2]
8         ntexts.append(res)
9     print(texts[6])
10
11
```

```
['william', 'cleveland', 'introduced', 'data', 'science', 'independent', 'discipline', 'extending', 'field', 'statistics', 'incorporate', 'advances', 'computing', 'data', 'article', 'data', 'science', 'action', 'plan', 'expanding', 'technical', 'areas', 'field', 'statistics', 'published', 'volume', 'april', 'edition', 'international', 'statistical', 'review', 'revue', 'internationale', 'de', 'statistique', 'report', 'cleveland', 'establishes', 'six', 'technical', 'areas', 'believed', 'encompass', 'field', 'data', 'science', 'multidisciplinary', 'investigations', 'models', 'methods', 'data', 'computing', 'data', 'pedagogy', 'to', 'evaluation', 'theory']
```

## 4. Creating phrases of words that frequently occur together (bigrams)

Bigrams are those words which occur together almost all the time. Example : New York, Machine Learning. Bigrams are created using phrases.

#### Creating bigrams

```
1 common_terms = ["of", "with", "without", "and", "or", "the", "a"]
2 x=ntexts
3 # Create the relevant phrases from the list of sentences:
4 phrases = Phrases(x, common_terms=common_terms)
5 # The Phraser object is used from now on to transform sentences
6 bigram = Phraser(phrases)
7 # Applying the Phraser to transform our sentences
8 all_sentences = list(bigram[x])
```

## 5. Creating word embedding using Gensim , Word2Vec and building a word2vec model.

The Gensim library provides a simple API to the Google word2vec algorithm which is used to create word embeddings.

Word embedding is one of the most popular representation of document vocabulary. It is capable of capturing context of a word in a document, semantic and syntactic similarity, relation with other words, etc.

```
model=gensim.models.Word2Vec(all_sentences,size=5000,min_count=2,workers=4>window=4)
model.save("final.model")
wrds=list(model.wv.vocab)
print(len(wrds))
```

## 6. Testing the model.

#### Testing

```
1 z=model.wv.most_similar("machine_learning")
```

```
1 print(z)
```

```
[('data', 0.15456914901733398), ('software', 0.1450301557779312), ('methods', 0.14181078970432281), ('used', 0.13762125372886658), ('learning', 0.1367097645998001), ('data_science', 0.13646116852760315), ('development', 0.1355130821466446), ('deep_neural', 0.1300312727689743), ('web', 0.1286322921514511), ('systems', 0.1274881362915039)]
```

#### Resume Parsino

## 7. Extracting resumes (using PyPDF) and converting to string

Resumes are stored in a folder and extracted one by one using PyPDF library and returned as a sequence of strings. The string is preprocessed and is further processed to create candidate profiles.

### Function to words from resume

```
1 import collections
2 def pdfextract(file):
3     pdf_file = open(file, 'rb')
4     read_pdf = PyPDF2.PdfFileReader(pdf_file)
5     number_of_pages = read_pdf.getNumPages()
6     c = collections.Counter(range(number_of_pages))
7     for i in c:
8         #page
9         page = read_pdf.getPage(i)
10        page_content = page.extractText()
11    return (page_content.encode('utf-8'))
```

## 8. Building candidate profile using model.most\_similar(skills), where skills is an array of required skills and creating a matcher using Spacy to match the words in resume to most\_similar(skills)

Spacy's Phrase matcher is used to match the array(obtained from word2vec) with the extracted text. It assigns each skill to a particular keyword and scores accordingly.

```
def create_profile(file):
    model=Word2Vec.load("final.model")
    text = str(pdfextract(file))
    text = text.replace("\n", "")
    text = text.lower()
    #print(text)
    #text=create_bigram(text)
    #print(text)
    #below is the csv where we have all the keywords, you can customize your own
    #keyword_dictionary = pd.read_csv(r'C:\Users\dell\Desktop\New folder\ML_CS\NLP\technical_skills.csv')
    stats = [nlp(text[0]) for text in model.wv.most_similar("statistics")]
    NLP = [nlp(text[0]) for text in model.wv.most_similar("language")]
    ML = [nlp(text[0]) for text in model.wv.most_similar("machine_learning")]
    DL = [nlp(text[0]) for text in model.wv.most_similar("deep")]
    #R = [nlp(text) for text in keyword_dictionary['R Language'].dropna(axis = 0)]
    python = [nlp(text[0]) for text in model.wv.most_similar("python")]
    Data_Engineering = [nlp(text[0]) for text in model.wv.most_similar("data")]
    print("*****")
    #print(stats_words,NLP_words)
    matcher = PhraseMatcher(nlp.vocab)
    matcher.add('Stats', None, *stats)
    matcher.add('NLP', None, *NLP)
    matcher.add('ML', None, *ML)
    matcher.add('DL', None, *DL)
    matcher.add('Python', None, *python)
    matcher.add('DE', None, *Data_Engineering)
    doc = nlp(text)
```

### Output

```

*****
KEYWORDS
Stats programming (1)
DE systems (1)
DE software (1)
Python data (3)
ML web (1)
*****DATAF*****
Keywords_List
0 Stats programming (1)
1 DE systems (1)
2 DE software (1)
3 Python data (3)
4 ML web (1)
['AmanSharma']
*****DATAF*****
Candidate Name Subject Keyword Count
0 amansharma Stats programming 1
1 amansharma DE systems 1
2 amansharma DE software 1
3 amansharma Python data 3
4 amansharma ML web 1
*****
KEYWORDS

```

## 9. Counting words under each category to build a candidate profile.

Counting words under each category and building the candidate profile

```

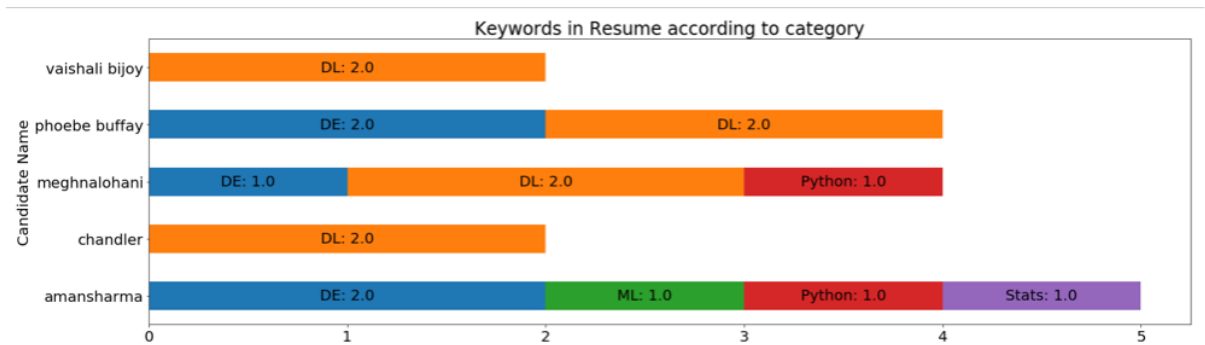
1 #Code to count words under each category and visualize it through Matplotlib
2 final_db2 = final_db['Keyword'].groupby([final_db['Candidate Name'], final_db['Subject']]).count().unstack()
3 final_db2.reset_index(inplace = True)
4 final_db2.fillna(0,inplace=True)
5 candidate_data = final_db2.iloc[:,1:]
6 candidate_data.index = final_db2['Candidate Name']
7 #the candidate profile in a csv format
8 cand=candidate_data.to_csv('candidate_profile.csv')
9 cand_profile=pd.read_csv('candidate_profile.csv')
10 cand_profile

```

	Candidate Name	DE	DL	ML	Python	Stats
0	amansharma	2.0	0.0	1.0	1.0	1.0
1	chandler	0.0	2.0	0.0	0.0	0.0
2	meghnalohani	1.0	2.0	0.0	1.0	0.0
3	phoebe buffay	2.0	2.0	0.0	0.0	0.0
4	vaishali bijoy	0.0	2.0	0.0	0.0	0.0

## 10. Printing and visualizing the candidate profile

The candidate profile is visualized through a bar graph using scores of each skill. So, the recruiter can easily interpret the candidate profile.



## CONCLUSION

The application is able to match each skill in the candidate resume to a particular keyword (Machine learning, Programming) based on semantic distance between the words, i.e. using Word Embeddings. Matching is done by Spacy's matcher and a score is created for each keyword. The final scores are visualized.

## FUTURE SCOPE

With a better refined corpus, the model can be made more accurate. Due to the unavailability of the required corpus, we created a small corpus using Sketch Engine, therefore the vocabulary is limited.

## REFERENCES

1. <https://machinelearningmastery.com/develop-word-embeddings-python-gensim/>
2. <https://www.shanelynn.ie/word-embeddings-in-python-with-spacy-and-gensim/>
3. <https://app.sketchengine.eu/>